Storypoint Problem Exploration - mulestudio

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1 Storypoint Prediction: Problem Exploration

1.1 Problem Statement

In modern agile development settings, software is developed through repeated cycles (iterative) and in smaller parts at a time (incremental), allowing for adaptation to changing requirements at any point during a project's life. A project has a number of iterations (e.g. sprints in Scrum). Each iteration requires the completion of a number of user stories, which are a common way for agile teams to express user requirements.

There is thus a need to focus on estimating the effort of completing a single user story at a time rather than the entire project. In fact, it has now become a common practice for agile teams to go through each user story and estimate its "size". Story points are commonly used as a unit of measure for specifying the overall size of a user story.

1.2 Problem Formulation

Input: A string of length N that contains a story's name and description $C = \{c_1, c_2, c_3, ..., c_n\}$. For each story, a set of text embeddings that contains features $E = \{e_1, e_2, e_3, ..., e_m\}$ extracted from C has been provided.

Output: A natural number P associated with the story point of that user story

1.3 Dataset Information

Text Embeddings: Text embeddings are a way to convert words or phrases from text into a list of numbers, where each number captures a part of the text's meaning. The dataset has been preprocessed and converted into two kinds of text embeddings. You can choose to work with either of them or both: - Doc2Vec: Input strings are transformed into fixed-length vectors of size 128. These vectors capture the semantic meaning of words and their relationships within a document. - Look-upTable: Input strings are transformed into fixed-length vectors of size 2264. These vectors are obtained via transforming each word in the input strings into an identifier number, then padded to the length of the longest sample.

Dataset Structure & Format: Storypoint Estimation Dataset is stored in 3 folders labeled *raw data*, *look-up*, and *doc2vec*. Within each folder are 3 CSV files for training, testing, validation. Each csv file has the following columns: - `issuekey` : The unique identifier for a story. - `storypoint`: The correct number of storypoint. - An embedding column (`embedding` or `doc2vec`) contains text embedding vectors. The raw data csv will not have this and instead contain two columns with story `name` and `description`.

1.4 Exploration

1.4.1 Raw data exploration

[ ]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.feature_extraction.text import CountVectorizer
```

Output exploration

[ ]:
```python
# Import raw data from the CSV file

project_name = 'mulestudio'

all_data = pd.concat([pd.read_csv('data/' + project_name + '/' + project_name +
 ↪'_train.csv'),
                      pd.read_csv('data/' + project_name + '/' + project_name +
 ↪'_valid.csv'),
                      pd.read_csv('data/' + project_name + '/' + project_name +
 ↪'_test.csv')])

print('Check the shape of the dataset', all_data.shape)
```

```
Check the shape of the dataset (732, 4)
```

[ ]:
```python
all_data.drop(['issuekey'], axis=1, inplace=True)
all_data.head()
```

[ ]:
```
                                              title  \
0                                  support requestreply
1   cannot import studio project git without errors
2                     changes java code get hot deployed
3    unable add response creating second flow mflow
4  namespaces xml view removed remove elements kind

                                         description  storypoint
0                               requestreply mockups          13
1  steps reproduce create simple mule studio proj…           3
2  java source changes dont get picked right auto…           5
3  unable add response creating second flow steps…           8
4  add element remove reference schema file remov…           8
```

First, let take a look at the distribution of the story point:

Interpretation of Skewness Values:

- **Skewness** $>$ **0**: Right-skewed distribution.
- **Skewness** $<$ **0**: Left-skewed distribution.

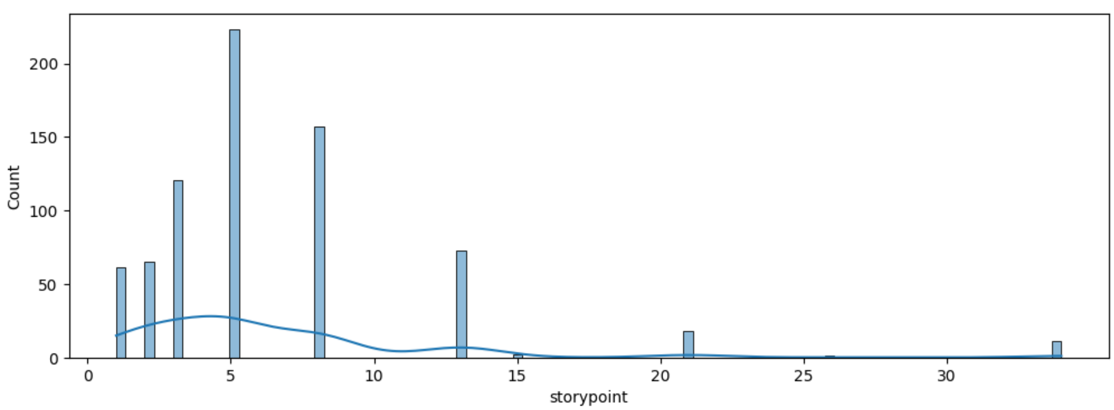
- **Skewness = 0**: Symmetrical distribution (like a normal distribution).

Interpretaion of kurtosis: - **Leptokurtic (Kurtosis > 3)**: The distribution has heavier tails and a sharper peak than the normal distribution. Data points are more likely to produce extreme values. The distribution has a higher peak and fatter tails. - **Platykurtic (Kurtosis < 3)**: The distribution has lighter tails and a flatter peak than the normal distribution. Data are fewer extreme values compared to a normal distribution. - **Mesokurtic (Kurtosis 3)**: The distribution has a similar kurtosis to the normal distribution, indicating a moderate level of outliers.

[ ]:
```python
# Draw a histogram of the story points
plt.figure(figsize=(12, 4))
plt.xticks(np.arange(0, max(all_data['storypoint']) + 1, 5))
sns.histplot(all_data['storypoint'], bins=100, kde=True)

print('Skewness:', all_data['storypoint'].skew())
print('Kurtosis:', all_data['storypoint'].kurt())
```

```
Skewness: 2.611965835103211
Kurtosis: 9.441787376635283
```



[ ]:
```python
tmp = pd.concat([all_data['storypoint'].value_counts(),
                 all_data['storypoint'].value_counts() / all_data.shape[0] *␣
 ↪100],
                axis=1, keys=['Counts', 'Percentage (%)'])
tmp.head(20)
```

[ ]:

	Counts	Percentage (%)
storypoint		
5	223	30.464481
8	157	21.448087
3	121	16.530055
13	73	9.972678
2	65	8.879781
1	61	8.333333

21	18	2.459016
34	11	1.502732
15	2	0.273224
26	1	0.136612

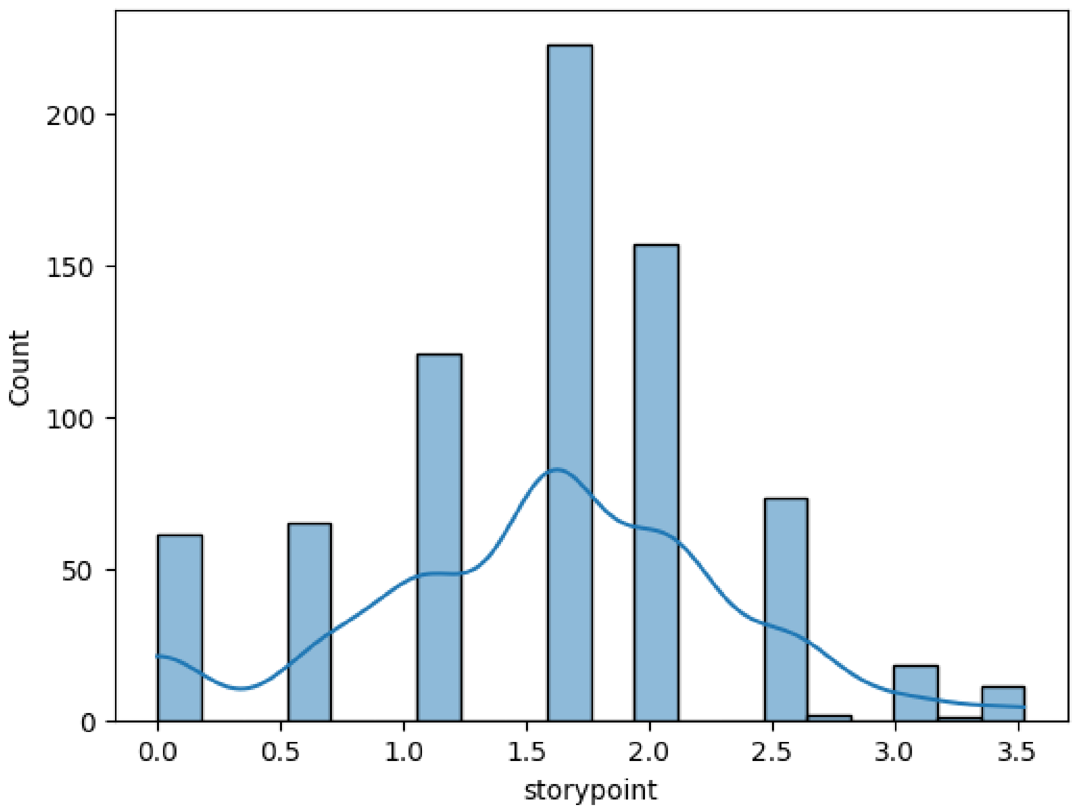
At the first sight, this data is bad. Then take a look at the statistic values, this data is even worse. Its distribution of the label is **right-skewed** and **leptokurtis**. This means if we use this to train model, the right side of the data can be the outliers and make the models become unsuable.

I will try 2 solutions: - Use log-scale on the label - Remove all the examples with label greater than a threshold (20, 30 or 40)

The first solution: logarithm magic

[ ]:
```
sns.histplot(np.log(all_data['storypoint']), bins=20, kde=True)
```

[ ]: <Axes: xlabel='storypoint', ylabel='Count'>



[ ]:
```
print('Skewness:', np.log(all_data['storypoint']).skew())
print('Kurtosis:', np.log(all_data['storypoint']).kurt())
```

```
Skewness: -0.17933884661052793
Kurtosis: 0.03990222241822439
```

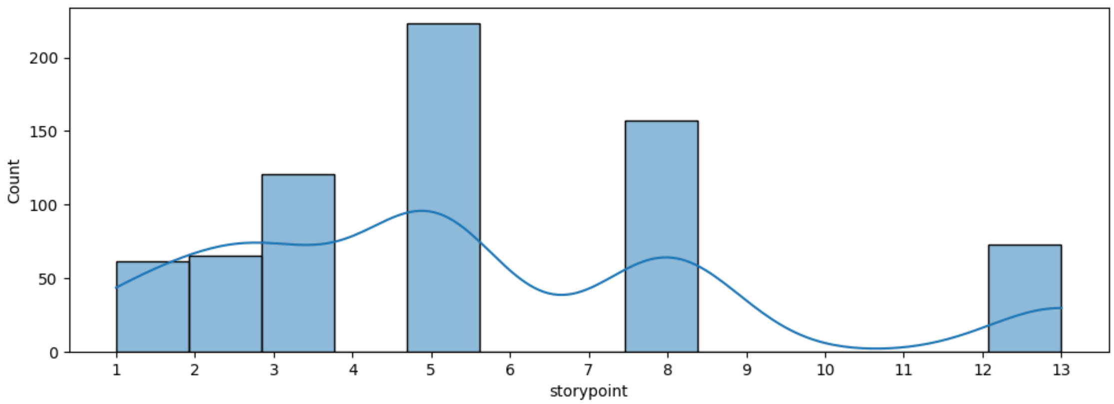
Using log-scale made the distribution a little bit better

The second solution: Dismantle and Cleave

[ ]:
```
threshold = 13 # This threshold means that we will take all the examples with␣
    ↪story points less than or equal to 20

new_data = all_data[all_data['storypoint'] <= threshold]
plt.figure(figsize=(12, 4))
plt.xticks(np.arange(0, max(new_data['storypoint']) + 1, 1))
sns.histplot(new_data['storypoint'], bins=threshold, kde=True)
print('Fitered percentage: ', round(1 - new_data.shape[0] / all_data.shape[0],␣
    ↪2) * 100, '%')
```

```
Fitered percentage:  4.0 %
```



Input exploration The input of this problem is 2 texts: title and description. First we will find some statistics:

[ ]:
```
title_lengths = all_data['title'].apply(lambda x: len(x.split(' ')))
print('Title analysis:')
print('   - Mean length:', round(title_lengths.mean()))
print('   - Min length:', title_lengths.min())
print('   - Max length:', title_lengths.max())

description_lengths = all_data['description'].apply(lambda x: len(x.split(' '))␣
    ↪if type(x) != float else 0)
print('Description analysis:')
print('   - Mean length:', round(description_lengths.mean()))
print('   - Min length:', description_lengths.min())
print('   - Max length:', description_lengths.max())
```

```
Title analysis:
   - Mean length: 6
```

```
   - Min length: 1
   - Max length: 16
Description analysis:
   - Mean length: 26
   - Min length: 0
   - Max length: 721
```

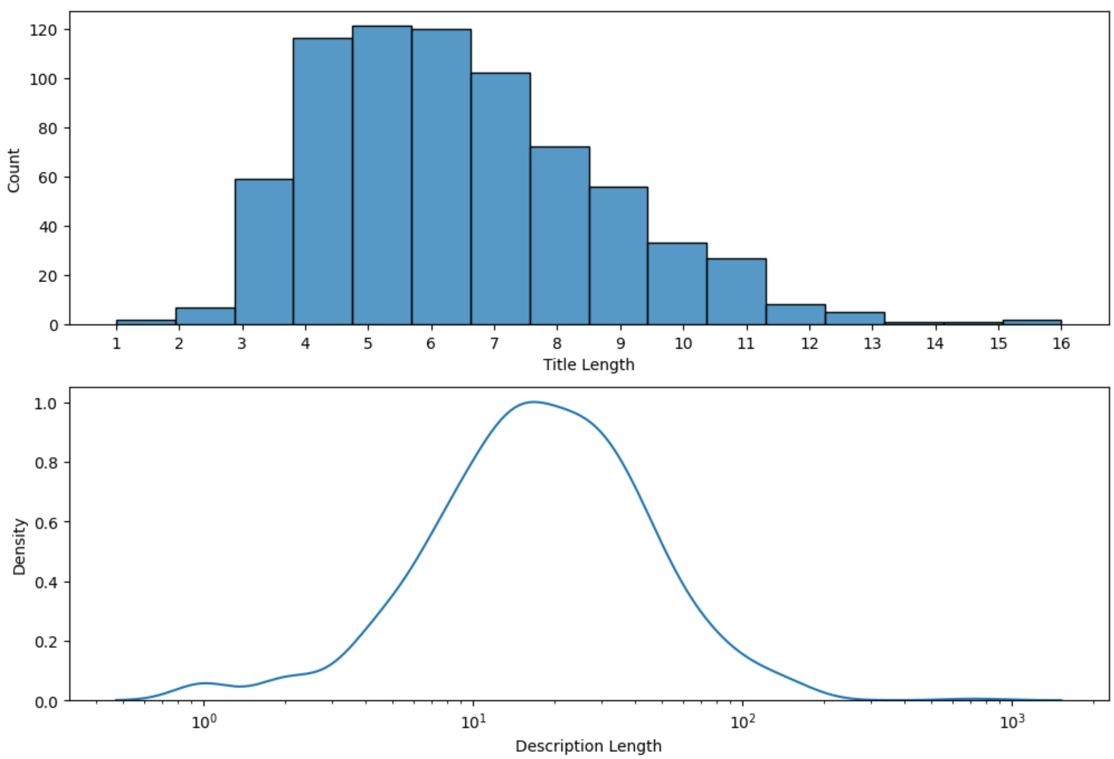
Plot the histogram of the title length and KDE of the description length (exclude 0):

[ ]:
```python
plt.figure(figsize=(12, 8))

plt.subplot(2, 1, 1)
plt.xticks(np.arange(0, max(title_lengths) + 1, 1))
plt.xlabel('Title Length')
sns.histplot(title_lengths, bins=max(title_lengths))

plt.subplot(2, 1, 2)
plt.xlabel('Description Length')
plt.xscale('log')
sns.kdeplot(description_lengths[description_lengths > 0])
```

[ ]:
```
<Axes: xlabel='Description Length', ylabel='Density'>
```



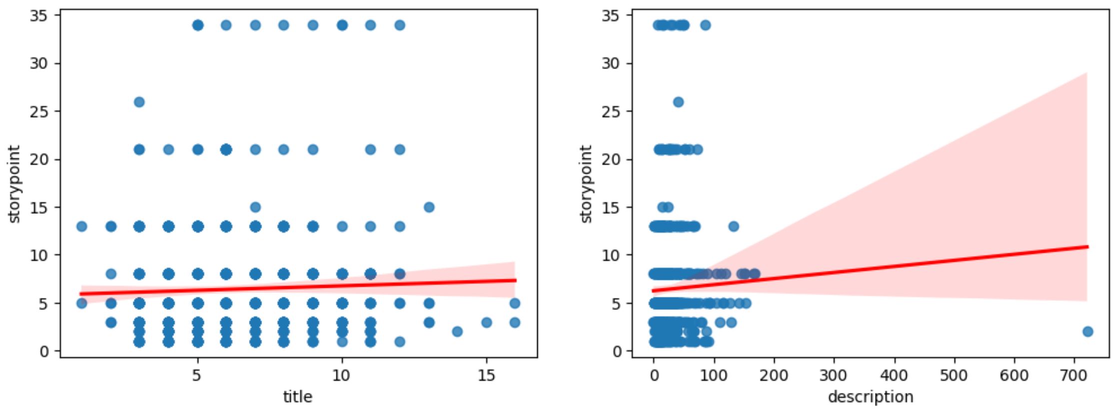
I think we should check the correlation between title length and description length:

[ ]:
```
plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.xticks(np.arange(0, max(all_data['title'].apply(lambda x: len(x.split('␣
↪')))) + 1, 5))
sns.regplot(x=all_data['title'].apply(lambda x : len(x.split(' '))),
            y=all_data['storypoint'],
            line_kws={'color': 'red'})

plt.subplot(1, 2, 2)
sns.regplot(x=all_data['description'].apply(lambda x : len(x.split(' ')) if␣
↪type(x) != float else 0),
            y=all_data['storypoint'],
            line_kws={'color': 'red'})
```

[ ]: <Axes: xlabel='description', ylabel='storypoint'>



In the left plot, we can see a little (really little) bit of corelation. In the right plot, the relation is easier to see but the deviation is too high, this could be noise.

Let dive deeper in the input:

Title analysis:

[ ]:
```
count_vectorizer = CountVectorizer()
count_vectorizer.fit(all_data['title'])

dictionary = pd.DataFrame(list(count_vectorizer.vocabulary_.items()),␣
↪columns=['word', 'frequency'])
dictionary.sort_values(by='frequency', ascending=False, inplace=True)
print(dictionary.shape)
dictionary.head(10)
```

```
(1349, 2)
```

```
[ ]:           word  frequency
     831      zuora       1348
     216       zoom       1347
     930       zips       1346
     603        zip       1345
     1200  yosemite       1344
     781       yaml       1343
     1049    xxxsql       1342
     1050  xxxquery       1341
     1323      xslt       1340
     233       xsds       1339
```

Description analysis:

```
[ ]: count_vectorizer = CountVectorizer()
     count_vectorizer.fit(all_data[all_data['description'].isnull() ==␣
      ↪False]['description'])

     dictionary = pd.DataFrame(list(count_vectorizer.vocabulary_.items()),␣
      ↪columns=['word', 'frequency'])
     dictionary.sort_values(by='frequency', ascending=False, inplace=True)
     print(dictionary.shape)
     dictionary.head(20)
```

```
(3665, 2)
```

```
[ ]:                   word  frequency
     2430             zuora       3664
     687               zoom       3663
     2616              zips       3662
     401                zip       3661
     2146              zero       3660
     1206             youre       3659
     654                yet       3658
     1868               yes       3657
     1816            yellow       3656
     1535             years       3655
     2133              yaml       3654
     2907            xxxsql       3653
     2908          xxxquery       3652
     3618              xslt       3651
     2775           xsitype       3650
     505   xsischemalocation       3649
     503         xsilocation       3648
     1323          xsdschema       3647
     2630    xsddocumentation       3646
     2626       xsdattribute       3645
```

Yet I don't find any thing special about the words in input except so many things are bad.

1.4.2 Solving strategies

My first intuitation in this problem is that the hard part is not on the algorithm we use, it is on the **embedding** part. Therefore, in case the given embedded datasets work not properly, I will use a better embedding method which is **Bidirectional Encoder Representations from Transformers (BERT)**. Also, I will try an old way to embedding the text too: **Bag of words**.

In conclusion, I will have 4 ways to embed the text: - doc2vec (already available) - Look up (already available) - Bag Of Words - BERT

About algorithm, I will try all the regression algorithm that may give a good result:

- Ridge Regressor
- Support Vector Regressor
- Random Forest Regressor
- Gradient Boosting
- XGBoost
- Lightgbm
- Blended

Maybe, we can change the problem to the classification problem with 100 labels (desparation confirmed). In the classification problem, I will use: - Support Vector Classifier - Softmax Regression (Multinomial Logistic Regression) - Random Forest - Adaboost - XGBoost

Thanks to the libaries, the implementation of all the algorithm shrinks to its minimum form.

At last, there is still a situation that all of mentioned model don't give a good result. This gamble is thrilling (hopeless).

"But would you lose?"

Nah, I'd win.